Renewable and Sustainable Energy Reviews 31 (2014) 762–777

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Current status and future advances for wind speed and power forecasting

Jaesung Jung*, Robert P. Broadwater

Department of Electrical and Computer Engineering, Virginia Polytechnic Institute and State University, 302 Whittemore Hall, Virginia Tech, Blacksburg, VA 24061-0111, USA

A R T I C L E I N F O

Article history:
Received 15 April 2013
Received in revised form
30 November 2013
Accepted 29 December 2013
Available online 22 January 2014

Keywords:
Wind speed
Wind power
Spatial correlation forecasting
Regional forecasting
Probabilistic forecasting
Offshore forecasting

A B S T R A C T

This paper presents an overview of existing research on wind speed and power forecasting. It first discusses state-of-the-art wind speed and power forecasting approaches. Then, forecasting accuracy is presented based on variable factors. Finally, potential techniques to improve the accuracy of forecasting models are reviewed. A full survey on all existing models is not presented, but attempts to highlight the most promising body of knowledge concerning wind speed and power forecasting.

Contents

* Corresponding author. Tel.: +1 540 577 6396; fax: +1 540 231 3362.
E-mail address: jjaesung@vt.edu (J. Jung).

1364-0321/$ - see front matter © 2014 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.rser.2013.12.054

1. Introduction

Wind power is one of the most rapidly growing renewable energy sources, and is regarded as an appealing alternative to conventional power generated from fossil fuel. This led to a collaborative effort to achieve 20% of U.S. electricity supplied from wind power by 2030 [1]. Although the integration of wind power brings many advantages, high penetration of wind power provides a number of challenges in power system operations and planning, mainly due to its uncertain and intermittent nature. In the electricity system the power supply must be equal to the power demand at all times. However, the variation of wind power output makes it difficult to maintain this balance.

One of the possible solutions to the balance challenge is to improve the wind speed and power forecasting. Research in the area of forecasting wind speed or the power produced by wind farms has been devoted to the development of effective and reliable tools and many different approaches have been proposed and reviewed in [2–13]. Accurate forecasting tools reduce operating costs and improve reliability associated with the integration of wind power into the existing electricity supply system [14–29].

There are different users of wind speed and power forecasts. These users not only need point forecasts but also the uncertainty of the forecast is essential for determining the size of the operating reserves necessary to balance the generation with load. For the market operator, the forecast of the total wind power production in a region is needed more than the individual wind plant forecast. For the system planner, it is essential to plan the installation of new wind turbines. The desired forecasting capabilities typically vary among user groups. This paper divides the forecasting methods into five categories: wind speed and power forecasting, spatial correlation forecasting, regional forecasting, probabilistic forecasting, and offshore forecasting.

A large amount of research has been directed toward the development of accurate and reliable wind speed and power forecasting models and many different approaches have been developed. However it is difficult to draw conclusions as to which model is the best because each model in use has significant site dependencies. Thus, a forecasting model may perform well at its site, but this does not guarantee that the model will work well at another site. This paper discusses forecasting accuracy based on variable factors that are used in the forecast.

Furthermore, several potential techniques for improving forecasting accuracy have been reported in the literature. These are also discussed and reviewed in this paper.

The paper is organized as follows. Section 2 presents an overview of existing wind speed and power forecasting approaches. In Section 3, the general forecasting accuracy is discussed. Some of the potential techniques to improve the performance of forecasting models are presented in Section 4. Finally, conclusions and future works are drawn in Section 5.

2. Overview of current wind speed and power forecasting

2.1. Wind speed and power forecasting

The basic role of wind speed and power forecasting is to provide information about the wind speed and power that can be expected in the next few minutes, hours, or days. Based on power system operation requirements, the forecast can be divided into four different horizons: very short-term (few seconds to 30 min), short-term (30 min to 6 h), medium-term (6–24 h), and long-term (1–7 days) [10,11]. Very short-term forecasts are used for turbine control and load tracking. Short-term forecasts are utilized for preload sharing. Medium-term forecasts are used for power system management and energy trading. Long-term forecast are used for maintenance scheduling of the wind turbines.

Research in the area of forecasting wind speed and the power produced by wind farms has been devoted to the development of effective and reliable tools and many different approaches have been proposed. These tools can be classified whether the terrain information at the location is used as an input or not. Two mainstream approaches are the physical and the statistical approach. In some models a combination approach is used in an attempt to integrate the advantages of both approaches. In this section an overview of existing wind speed and power forecast approaches is presented.

2.1.1. Physical forecasting approach

The physical approach to forecasting, in contrast to statistical approach, uses the detailed physical description to model the on-site conditions at the location of the wind farm [7,30]. The basic operation of a physical approach is illustrated in Fig. 1.

It carries out the refinement of the Numerical Weather Prediction (NWP) data to take into account the on-site conditions by the downscaling method, which are based on the physics of the lower atmospheric boundary layer. The downscaling method requires the detailed physical descriptions of the wind farms and their surroundings, including: description of the wind farm (wind farm layout and wind turbine power curve, etc.) and description of the terrain (orography, roughness, obstacles, etc.). Then, the refined wind speed data at the hub height of the wind turbines is plugged into the corresponding wind power curve to calculate the wind power production. If the on-line data is available, model output statistics are performed to reduce the error of the forecast. Contrary to the statistical approach, the physical approach does

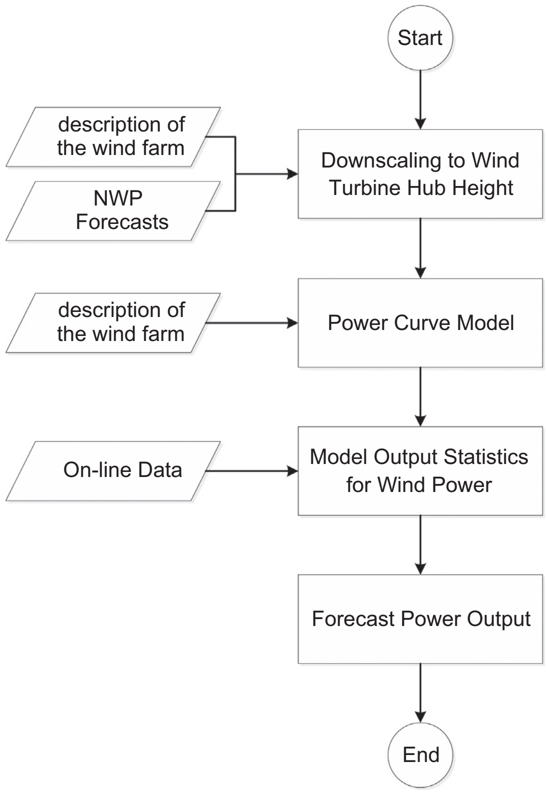


Fig. 1. The physical approach to forecasting wind speed and power.

not require training input from historical data. However, acquiring the physical data is one of the main drawbacks of the approach.

A number of physical approaches have been introduced [2,7,8,31,32]. The *Prediktor* is developed by the Risoe National Laboratory in Denmark. It uses Wind Atlas Analysis and Application Program (WAsP) and PARK program to take the local conditions into account by using the NWP forecast from High Resolution Limited Area Model (HIRLAM) [33–35]. The *Previento*, developed by the University of Oldenburg in Germany has a similar physical approach but uses a different NWP forecast from *Lakelmodell* of the German Weather Service [36]. The *LocalPred* is developed by CENER – National Renewable Energy Centre in Spain. It involves adaptive optimization of the NWP forecast, time series modeling, meso-scale modeling with MM5, and power curve modeling [37]. The eWind, developed by AWS TrueWind Inc. in the USA, has a similar physical approach with *Prediktor* but uses a high-resolution boundary layer model (ForeWind) as a numerical weather model to take the local conditions into account [38].

The physical approaches are based on the models using the fundamental physical principles for conservation of mass, momentum, and energy in air flows. These models address computational fluid dynamics (CFD) for simulating the atmosphere. Although there are many CFD models available, they are all based on the same basic physical principles. They differ in how the grids are structured and scaled, and how the numerical computations are performed.

In the majority of cases the statistical approaches provide good results in short-term, medium-term, and long-term forecasting. However, in the very short-term and short-term horizon, the influence of atmospheric dynamics becomes more important, and in these cases the use of physical approaches becomes essential.

2.1.2. *Statistical forecasting approach*

The alternative main approach for wind speed and power forecasting is based on statistical modeling. The statistical approach represents the relation between wind power or speed forecasting and explanatory variables including NWPs and on-line measured data [7]. The general form of the model is illustrated in Fig. 2.

The statistical approach generally uses previous history data to build the statistical model. This model uses NWP forecast for time $t+k$ and on-line measurement at time t to forecast the present over the next few hours. It is easy to model and inexpensive. However, contrary to the physical approach, the statistical approach requires historical data to train the statistical model. Many different approaches are employed [2,3,5,6,11,13]. Some of the representative statistical approaches are reviewed in this section.

2.1.2.1. Conventional statistical approach. In the conventional statistical approach a time series model is applied to forecast future wind power or speed. According to the forecasting process, which was proposed by Box–Jenkins, this model is divided into four main steps to make a mathematical model of the problem including model identification, model estimation, model diagnostics checking, and forecasting. Several types of time series models may be considered, including autoregressive model (AR), moving average model (MA), autoregressive moving average model (ARMA), and autoregressive integrated moving average model (ARIMA). The general form of the model is

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{1}$$

where X_t represents the forecasting parameter at time t, φ_i is the autoregressive parameter, θ_i is the moving average parameter, c is the constant, and random variable ε_t is the white noise. This model represents the ARMA model having the autoregressive model of order p and the moving average model of order q (ARMA(p,q)). If the order of the moving average model (q) is zero, it represents the autoregressive model of order p (AR(p)). If the order of the autoregressive model (p) is zero, it represents the moving average model of order q (MA(q)). The ARIMA model is a generalization of an ARMA model.

The ARMA model is used for wind power forecasting in U.S. wind farms in [39,40]. Some of the models offer improvements over the persistence model but some are not by changing the order of AR and MA. The performance of the model is highly dependent on the parameters of the model.

The Improved Time Series Method (ITSM) based on ARIMA is used in [41]. The sub-wind speed series obtained from the wavelet decomposition is forecasted and then the aggregate calculation of the sub-series is performed to obtain the final wind speed forecast. The simulation results indicate that the proposed method improves the accuracy of forecasting over the classical time series model and the neural network model.

The Autoregressive Conditional Heteroscedastic (ARCH) model is combined with the ARIMA model to consider the heteroscedasticity effect of the residual series [42]. The ARIMA–ARCH model is used to forecast the sub-wind speed series obtained from the wavelet decomposition. The final wind speed forecasting is the sum of these forecast values. The results show that it can improve the accuracy of the forecasting. In [43], the ARIMA–ARCH model is used to forecast wind speed itself. It is shown that the ARIMA–ARCH model shows better performance than the ARIMA model.

To deal with the non-stationary of wind speed, wind speed data are transformed to a Gaussian distribution and standardized to remove the non-stationary in [44]. The parametric AR model is then applied to the hourly wind speed data and is updated during the real-time operation by a recursive least squares algorithm. The method is validated by using the wind speed data from a wind power site.

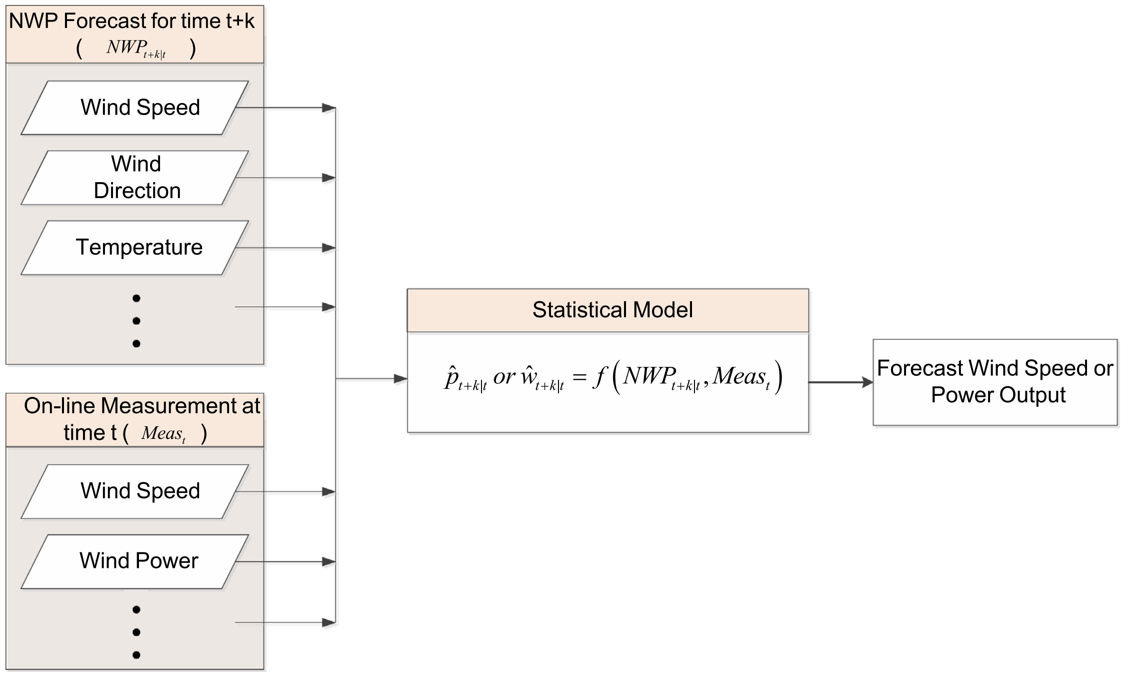


Fig. 2. The statistical approach to forecasting wind speed and power.

In [45], the ARMA model is used to forecast the tuple of wind speed and direction. Four different approaches are proposed and their performances are compared; component, traditional-linked ARMA, vector AR (VAR), and restricted VAR approaches. The component approach is better than traditional-linked ARMA for wind direction forecasting but not for wind speed forecasting. The VAR approach offers better performance in wind direction and close performance in wind speed comparing with traditional-linked ARMA. There is little difference in terms of forecasting performance between VAR and restricted VAR approaches.

The AR model using a Bayesian approach is used to forecast the wind speed in [46]. First, Box-Cox transformation is performed to correct the non-normality of the wind speed. Then, the Markov Chain Monte Carlo (MCMC) simulation is performed to estimate the AR model parameters, which can then be used to forecast wind speeds. It shows the great potential and possible improvements of a Bayesian framework.

In summary, conventional statistical approaches are based on classical linear statistical models such as AR, MA, ARMA, and the Box–Jenkins approach, where Box–Jenkins is based on ARIMA or seasonally adjusted ARIMA models, also known as SARIMA models. However, the references show that the forecasting accuracy can be improved depending on the model parameters that are selected.

The conventional statistical approaches are mostly aimed at very short-term and short-term forecasting. These models are easy to formulate and are capable of providing timely forecasts. As forecasting accuracy is improved, conventional statistical approaches are often used as a reference model.

2.1.2.2. Artificial Neural Network approach. Another approach is Artificial Neural Networks (ANN). The NWP forecasts and further meteorological variables are transformed into the wind power or speed forecast by ANN which has been trained by the large sets of historical data in order to learn the dependence of the output on input variables. The general ANN approach for wind speed and power forecast is shown in Fig. 3.

ANN is one of the widely used statistical approaches for wind speed and power forecasts. It consists of an input layer, one or more hidden layers, and an output layer. Each layer has a number of artificial neurons, and it uses a connectionist approach to connect the neurons to the neurons of the previous layer. This approach is able to model the complex non-linear relationship between the input and output layers through a training and learning process. This approach does not require explicit mathematical expressions as used in the physical and statistical approaches reviewed previously. Furthermore, it has the ability of self-learning, self-organizing and self-adaption.

In [47], the ANN methodology using the Markov Chain approach is proposed for very short-term wind speed forecast. The Markov Chain is applied to modify the preliminary forecast obtained from ANN according to the long-term patterns. A data set with 2.5 s resolution is used to evaluate the performance. The results show the effectiveness of the proposed method.

The ANN methodology using Particle Swarm Optimization (PSO) is proposed for short-term wind power forecast in [48]. PSO is employed to select the input variable from the several nearby locations. The proposed method shows the reduction of the forecast error comparing with ANN.

Furthermore, the forecast method composed of a new Enhanced Particle Swarm Optimization (EPSO) technique and Modified Hybrid Neural Network (MHNN) is proposed to have high learning capability and avoid the overfitting problem and trapping in local minima and dead bands in [49]. The effective two-stage feature selection technique, enhanced Mutual Information (MI), is applied to select the most informative candidate inputs by filtering out both irrelevant and redundant candidate inputs for the forecast method. The results confirm the validity of the developed approach.

In [50], the forecast method based on Ridgelet Neural Network (RNN) is proposed as the forecast engine. The inputs of the forecast engine are selected by the Mutual Information (MI) based feature selection component among the set of candidate inputs. A New Differential Evolution (NDE) algorithm with novel crossover operator and selection mechanism is proposed to train the RNN. The results show the effectiveness of the proposed method.

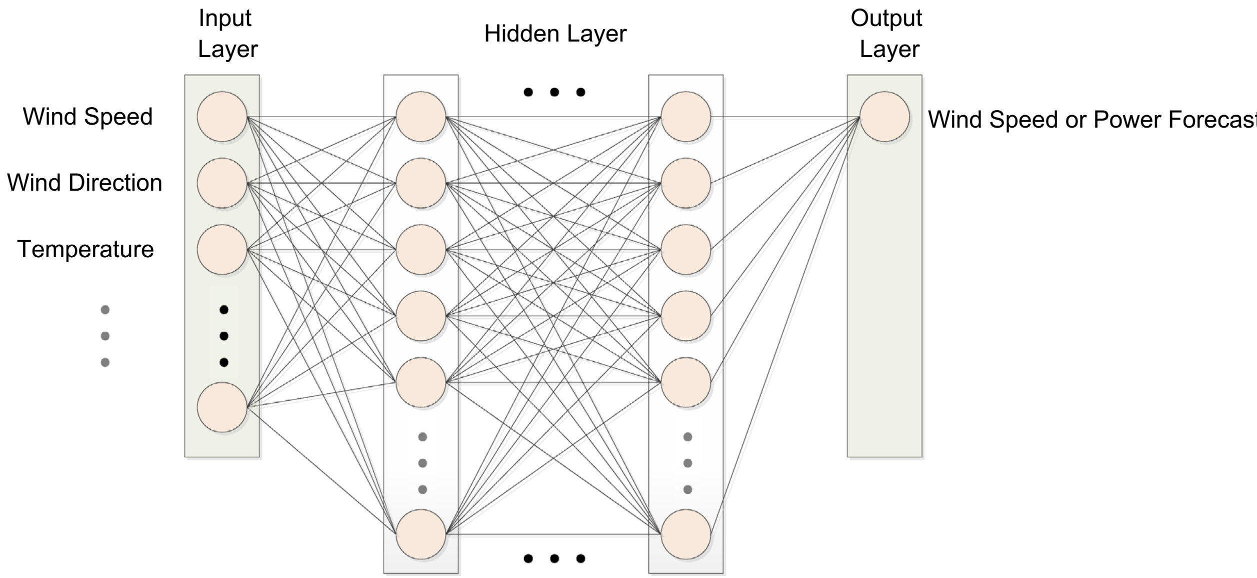


Fig. 3. ANN approach for wind speed and power forecast.

In [51], a comprehensive comparison study of typical three types of ANN approach is performed; Feed Forward Back-Propagation (FFBP), Radial Basis Function (RBF), and Adaptive Linear Element (ADALINE) approaches. It is found that different inputs and learning rates, as well as model structures, directly influence the forecast accuracy. Furthermore, none of the approaches outperform others universally based on the evaluation criteria even for the same wind dataset.

Complex-Valued Neural Network (CVNN) is proposed for the wind power forecast in [52]. The CVNN used the wind vector (both wind speed and direction) rather than real-valued data as an input. The results show the improvement in the forecast accuracy than Real-Valued Neural Network (RVNN).

In [53], an ANN approach in conjunction with the adaptive Bayesian learning and the Gaussian process approximation is proposed for very short-term wind power forecast. The Bayesian framework is employed updating to calculate the posterior probability distribution for the weights of the model. The Gaussian process approximation makes the calculation of this posterior probability possible to solve an integration problem of the Bayesian learning. The Bayesian framework provides not only point forecast but also the interval about the forecast.

A three-layered Feed-forward NN trained by the Levenberg–Marquardt algorithm is considered to forecast the wind power sub-series by Wavelet Transform (WT) in [54]. The obtained forecast sub-series reconstruct the future wind power series by inverse WT. The proposed approach is compared with the reference to demonstrate its effectiveness regarding forecasting accuracy and computation time. Similarly, in [55], Adaptive Wavelet Neural Network (AWNN) is carried out to forecast the wind speed in stage-I. Then, Feed-forward Neural Network (FNN) is used to transfer the wind speed forecast to the wind power forecast in stage-II.

In [56], standard multilayer Feed-forward Neural Network (FNN) is employed to forecast the wind speed. The non-linear and non-stationary wind speed series is first decomposed into a finite and often small number of Intrinsic Mode Functions (IMFs) and one residual series to obtain the stationary data series using the Empirical Mode Decomposition (EMD). FNN is performed to forecast the decomposed sub-series except the high frequency, whose input variables are selected by Partial Autocorrelation Function (PACF). Finally, the forecast sub-series are summed to reconstruct the forecast of wind speed series. The results show that the proposed approach outperforms the reference. Furthermore, a similar approach based on ANN using EMD is found in [57].

Generalized Feed-forward Neural Network (GFNN) is used to forecast the annual wind speed probability density distribution in [58]. The same parameters required by the Weibull function are used as inputs. The proposed method shows better accuracy to forecast the wind speed probability density distribution than the Weibull function.

Multilayer Feed-forward Neural Network (MFNN) is used to forecast a day-ahead wind power forecasting in [59]. The NWP model is established by coupling the Global Forecasting System (GFS) with the Weather Research and Forecasting (WRF) System. Furthermore, the Kalman filter is integrated to reduce the systematic error from WRF. The proposed method is proved to be successful by the simulation.

In [60], Kernel Ridge Regression (KRR) with active learning is performed for wind speed forecast. The active learning acts as a smart sample selector capable to yield compact forecast models and also to filter out noisy training samples. Three active learning methods to construct the training set for KRR are proposed; Pool of regressors (PAL), Distance from the closest training sample (DAL), and Residual regression (RSAL). The experimental results show that smart collection of training samples can be of benefit for wind speed forecast.

ANN has been a good selection for wind speed and power forecasting. ANN is able to model a complex non-linear relationship and extract the dependence between the input and output through the learning process. It is simple to construct and only requires short development times, and does not require explicit mathematical expressions. ANN can be designed by setting up the network structure and then selecting a learning algorithm.

The first step with ANN is to choose the network structure, where network structures derive from two basic classes: 1 – A feed-forward topology where information flows in only one direction, from inputs to outputs; 2 – A recurrent topology where information flows in both directions, from input to output and also from output to input.

The second step with ANN is to select the learning algorithm and to learn the proper response. This is achieved with three learning paradigms: 1 – Supervised learning that sets ANN parameters from training data; 2 – Un-supervised learning that sets ANN parameters based on given data and a cost function; 3

– Reinforcement learning that sets ANN parameters, where data is generated by interactions with the environment. Each learning paradigm has many learning algorithms. Some commonly used algorithms include evolutionary methods, gene expression programming, simulated annealing, expectation-maximization, non-parametric methods, and particle swarm optimization.

2.1.2.3. ANN–Fuzzy approach. The Fuzzy logic approach is a non-linear mapping of input variables into the output by using numerical and linguistic values Fuzzy rather than fixed and exact. It used soft linguistic variable (small, medium, and large) and a truth variable that ranges in degree between 0 and 1. The Fuzzy logic approach is employed when the system is difficult to model accurately but an inexact model is available, because it allows to use the approximate values and incomplete or ambiguous data. However, using the Fuzzy logic approach alone is not satisfying because of its weak learning ability.

The ANN–Fuzzy approach refers to combination of ANN and Fuzzy logic approaches. ANN is based on the learning and connectionist structure that performs well in low-level computation with raw data. However, Fuzzy logic performs well with the human-like reasoning in high-level computation. Therefore, the combination of two approaches offers a promising approach to forecast the wind speed and power by compensating their weakness each other.

In [61], ANN is combined with Fuzzy logic approach in order to optimize the best use of the NWPs. First, the ANN model provides the preliminary forecast of wind power based on NWPs. Then, the Fuzzy model estimates the quality of the forecasts provided by NWPs. Finally, this is exploited by an ANN model to provide the final forecasts. The simulation results show the validity of the proposed method.

The hybrid Wavelet Transform (WT)–Particle Swarm Optimization (PSO)–Adaptive Network based Fuzzy Inference System (ANFIS) approach (hybrid WPA approach) is proposed for short-term wind power forecasting in [62]. The wavelet transform is performed to convert a wind power series in a set of constitutive sub-series. The transformed sub-series are separately forecasted by the ANFIS. The PSO is used to adjust the parameters of the membership function in ANFIS. The hybrid WPA approach outperforms seven other reference approaches.

The Simultaneous Perturbation Stochastic Approximation (SPSA)-based Multilayer Feed-forward Neural Network (MFNN) with Fuzzy inputs algorithm is presented in [63]. The SPSA is employed to achieve the training task of the MFNN. The inputs for the MFNN are modeled by triangle fuzzy numbers. A better performance of the proposed method is shown than the reference method. However, it cannot be used for multistep forecasting.

ANN–Fuzzy approaches are complementary tools in building intelligent forecasting systems. While ANN performs well in low-level computational structures, Fuzzy logic deals with reasoning incorporated in the higher-level computational structures. Merging of the ANN approach and the Fuzzy logic approach into one integrated system offers a promising approach to building wind speed and power forecasting systems.

2.1.2.4. Etc. A Gaussian-Process-based method for forecasting the upper and the lower bounds of wind speed as well as the average is proposed in [64]. It makes use of the kernel machine technique and the Bayesian estimation. The simulation results show that they provide the better forecasting in consideration of the uncertainty than the reference. Furthermore, the advanced Gaussian-Process-based method, called the Sparse Heteroscedastic Gaussian Process (SPHGP) is proposed in [65]. This method is developed to make up the misestimation of the noise level from standard GP and reduces the computational costs from HGP. The $\ell_{1/2}$ regularizer is employed for the sparsification. The simulation results demonstrate the effectiveness of the proposed method.

In [66], the modified Taylor Kriging (TK) method for forecasting wind speed time series is proposed. The original TK method is developed for the spatial estimation. In this paper, the original TK method is properly modified for the time series forecasting. The simulation results indicate that the proposed method outperforms the ARIMA method.

The Grey forecasting model (GM) is presented for short-term wind speed forecast in [67]. The Grey model is designed for the system analysis being characterized by inadequate information. The GM(1,1) Grey model, a single variable first-order Grey model, is used. The simulation results demonstrate the efficiency of the proposed model.

In [68], two-stage hybrid network with Bayesian Clustering by Dynamic (BCD) and Support Vector Regression (SVR) is proposed. First, BCD clusters the input training dataset into several subsets with similar dynamical properties. Then, SVRs is used to model the training data in each subset having similar property. Experiments and comparisons with the persistence method demonstrate the effectiveness and efficiency of the proposed method.

The forecasting of three-dimensional wind field is considered in [69]. To exploit the available second order statistics, the augmented quaternion statistics is employed and the adaptive Widely Linear Quaternion Least Mean Square (WL-QLMS) algorithm for the forecasting is used to allow for both three-dimensional wind model and the fusion of atmospheric parameters. It is shown that additional information from the vertical wind speed and atmospheric parameters assist in providing better forecast.

In [70], the Bayesian Model Averaging (BMA) approach with Markov Chain Monte Carlo (MCMC) is proposed for developing the long-term wind speed distribution. The derived BMA probability density function (PDF) is an average of many candidate models included in the model space weighted by their posterior probabilities over the sample data. The case studies reveal that none of reference distribution outperforms others; however, the BMA distribution is always suitable to describe the wind speed distribution with high accuracy.

The forecasting model integrating the concepts of structural breaks and Bayesian inferences is proposed for very short-term wind speed forecasting in [71]. It allows prior information about the wind speeds to be incorporated into the model and somehow boosts forecasting performance by considering structural breaks. The computational results confirm the advantages of the proposed method. However, there are several limitations; for example, the computing efficiency is not high and the size of training sample is not large enough. Further research is needed to cure these limitations.

In [72], First-order and Second-order Adaptive Coefficient (FAC and SAC) methods are used to wind speed forecasting. Particle Swarm Optimization (PSO) is employed to select the most suitable parameter of FAC and SAC methods. Furthermore, Seasonal Exponential Adjustment (SEA) is employed to decompose the wind speed data into seasonal and trend components. Different combinations of these techniques are simulated. The combination obtains higher forecasting accuracy than the single FAC and SAC.

Data mining approaches in wind energy system have more attention in recent years [12]. The time series models are built with data mining algorithms for the short-term forecasting in [73]. Five different data mining algorithms are employed; the Support Vector Machine Regression (SVMreg), Multilayer Perceptron (MLP), M5P tree, Reduced Error Pruning (REP) tree, and the bagging tree algorithms. The computational results of all time series models and data mining algorithms are compared and

discussed. Furthermore, this approach is applied to forecast the wind power ramp rates in [74]. One of the disadvantage of the proposed approach is that the time series model uses its own previously forecasted value. Therefore, the forecast accuracy decreases when the number of forecast steps increase. In [75], a data mining approach is expanded to forecast both short-term and long-term period. Furthermore, an advanced model, the ANN approach, is employed. The simulation results show that the model generated by an ANN outperforms all other models for both short-term and long-term forecast.

The frequency domain approach is introduced for characterizing the wind speed patterns in [76]. This approach separates the discrete waveform into a sum of sinusoids of different frequencies from wind speed patterns. It shows a potential to forecast future wind speed patterns with better accuracy than time domain. Furthermore, it also shows a potential to estimate the wind speed patterns for a target location using available data from the reference site. It is necessary to develop the appropriate forecasting system using the components obtained from the frequency domain approach.

2.1.3. Combination approach

The basic idea of the combination approach is to combine different approaches, retaining advantages of each approach. The desire is to improve the forecast accuracy, but combining forecasts does not always perform better than the best individual forecasts. However, in some cases it is viewed as less risky to combine forecasts than to select an individual forecast [77]. In this section, the combination forecasting method is only reviewed. The combination of input data (NWPs) is discussed in Section 4.

Several approaches have been developed based on the combination of various models. The ANN–Fuzzy approach discussed in the previous section is one of the combination approaches. In [78], the final forecast is made through an adaptive linear combination of the alternative forecasts, where the weights given to each forecasting methods are based on their forecasting performance. For the combination, nine different time series models are considered by varying the model parameters. The proposed combination shows better performance than individual forecasts.

The Anemos project considers the combination method, called Adaptive Exponential Combination (AEC) in [79]. In the first step, several combination methods are used, AEC being one of them. In the second step, the AEC method is used to combine the alternative combinations of the first step. The results show the usefulness of the proposed method.

In [80], a Multiple Architecture System (MAS) for wind speed forecasting is proposed. The different regression algorithms are considered as candidate models for making up the ensemble forecast; the Multiple Linear (MLR)-based regression, the Multilayer Perceptron (MLP) neural networks, Radial Basis Functions (RBF) neural networks, and Support Vector Machines (SVM) regression. Three combination strategies are explored; simple average, weighted average, and non-linear fusion by means of an ANN method. The proposed combination strategies improve the performance with respect to the single forecast.

In [81], two types of univariate statistical forecasting models based on the Least Squares-Support Vector Machine (LS-SVM) are proposed: the univariate LS-SVM model and the hybrid model of ARIMA and LS-SVM model. The hybrid approach is designed to capture both the linear ARIMA modeled and the non-linear patterns modeled by LS-SVM. However, there are no significant improvements between LS-SVM and the hybrid model.

The combination approach between the Radial Basis Function (RBF) neural networks and persistence methods is considered in [82]. The experimental results show that the RBF method is better for monotonically wind speed changes while the persistence method is more suitable for random data with white noise. The simulation results demonstrate improvements in the combination approach.

In [83], two combination approaches, namely ARIMA–ANN and ARIMA–SVM, are proposed. The ARIMA method is employed for modeling the linear characteristics and the ANN or SVM methods are employed for modeling the non-linear characteristics. The results show that the combination is viable for forecasting both wind speed and wind power. However, the combined approaches do not always outperform the single method. A similar combination approach is also presented in [84].

In [85], two combination approaches are proposed; ARIMA–ANN and ARIMA–Kalman. ARIMA is used to decide the best structure of the ANN model and to obtain the best initial parameters of the Kalman model. Both combination approaches have good performance, which can be applied to non-stationary wind speed forecasting.

The Bayesian Model Averaging (MBA) approach is proposed to combine the wind speed forecasts obtained from different ANN models in [86]. Three different ANN models are considered; Adaptive Linear Element (ADALINE) network, Back-Propagation (BP) network, and Radial Basis Function (RBF) network. The BMA approach weights individual forecasts based on their posterior model probabilities, with the better performing forecasts receiving higher weights than the worse. The simulation results show the effectiveness of the proposed combination approach.

In [87], the combination of the Soft Computing Models (SCMs) and Similar Days (SD) methods is considered. Three SCMs models are considered, including Back-Propagation Neural Network (BPNN), Radial Basis Function Neural Network (RBFNN), and Adaptive Neuro-Fuzzy Inference System (ANFIS). The average of a selected number of similar wind speed days from SD methods is used for the input of SCMs and the application of SCM refines the results to obtain the final wind speed forecast. The simulation results show that all evaluated SCMs incur some level of performance improvement with the addition of the SD model. Furthermore, the SD–ANFIS model outperforms all other individual and combined models.

The combination between Seasonal ARIMA (SARIMA) and Least Square Support Vector Machine (LSSVM) is developed to forecast the average monthly wind speed in [88]. The SARIMA model is developed by using training data and the LSSVM model is developed to describe the residuals from the SARIMA model. The simulation results show that the proposed method is simple and efficient.

The main objective of the combination approach is to improve performance by taking advantage of the strengths of each modeling approach. Combinations can consist of physical and statistical or alternative statistical approaches. The advantage of combining results from different modeling approaches is improved forecast accuracy. Furthermore, the combination of models reduces risks during extreme events such as storms, where some model types may have significant forecasting errors.

2.2. Spatial correlation forecasting

Typically, wind speed and power forecasting refers to the future, and the forecast horizon depends on power system operation requirements. Spatial correlation forecasting, on the other hand, is mostly used for characterizing the wind resource at the site where sufficient information is not available but a neighboring measuring station is available. It is a useful indicator when performing wind energy potential assessments at sites without wind measurements.

Several approaches can be found regarding the problem of spatial correlation forecasting. The most commonly used approach is the Measure-Correlate-Predict (MCP) method [89]. It is widely used for future wind integration studies. The method is used for the long-term wind data at the target site using the wind data obtained from the reference site. Four different MCP methods are introduced: Linear Regression, Matric MCP, Weibull Scale, and Wind Index MCP model. It is found that all perform well, but the performance is of course dependent upon the condition of the available data.

Furthermore, in [90], the MCP method is used to forecast the long-term wind speed and then, the Monte Carlo based numerical simulation is performed to utilize the probability models at the target site. This model is used for assessing the uncertainty of overall wind energy potential prior to the construction of wind turbines. For the case study it was found that the method effectively evaluated the expected annual energy production at the site.

The Bayesian hierarchical model is developed to characterize the wind resource at the desired location using the known resource [91]. The hierarchical model has two levels. The wind speed data from the reference site is defined as the sum of a temporal, a spatial, and error components together at the first level. At the second level, a temporal and a spatial component are modeled as a first order random walk and a multivariate normal distribution respectively. It is found that the Bayesian inference can be a useful tool in spatial correlation forecasting.

In [92], the wind speed at "upwind" remote sites can be used for forecasting at "downwind" sites. The ANN approach is used to forecast the wind speed at the target site using the "upwind" and "downwind" site measurements. It is found that the short-term wind speed forecasting is improved when the recent measurements from the reference site are used.

In [93], the ANN approach is used to estimate the wind speed at the target site using the wind speed at a strong correlation site among nearby sites. A high value of the Sample Cross Correlation Function (SCCF) indicates the strongest correlation site. The simulation results indicate that higher SCCF values between two sites leads to better wind speed estimates. However, this method, contrary to other methods, requires the measurements from both the target and reference sites to calculate their SCCF.

A Takagi, Sugeno, and Kang (TSK) Fuzzy approach is proposed to forecast the wind speed and power at the target site using the wind speed and direction measured at neighboring sites in [94]. The Genetic Algorithm (GA) based learning scheme is employed to achieve the training task of the model. The performance is evaluated at various terrain cases and demonstrates significant improvements over the persistent model.

In [95], a method for long-term wind speed and power forecasting is proposed by using the NWPs provided at nearby sites of the wind park. Three types of local recurrent neural network models, depending on the neuron dynamic model, are employed: the Infinite Impulse Response Multilayer Perceptron (IIR-MLP), the Local Activation Feedback Multilayer Network (LAF-MLN), and the Diagonal Recurrent Neural Network (DRNN). Furthermore, two learning schemes for updating the weights of the model are employed; the Global Recursive Prediction Error (GRPE) and the Decoupled RPE (DRPE). It is shown that the proposed methods outperform the static and the persistence models.

The ANN approach is used to estimate the wind speed at a target station in [96]. The wind speeds recorded at neighboring measuring stations are used as signals for the input layer of the model. It is found that as the number of reference stations increase, the estimation errors tend to decrease. Furthermore, when the wind direction is used as an input, greater error reduction is achieved than when the wind direction signal is omitted.

Being different from traditional wind speed and power forecasting, spatial correlation forecasting takes into account the spatial relationship of wind speed and power from different sites. The spatial correlation forecasting requires wind speed and power measurements from multiple spatial correlated sites, where the measurements often involve time delays. The measurements and their time delays adds complexity and cost to the implementation of spatial correlation forecasting. Spatial correlation forecasting can either employ physical models, which take into account the terrain information, or statistical models, which take spatial correlation information into account.

2.3. *Regional forecasting*

Regional forecasting is to forecast aggregated power output from a region where a number of wind turbines are sited. The regional forecasting is required for the market operator to estimate the total wind power production in a region. It provides a faster approach than calculating the sum of the wind power forecast from each wind farm. Furthermore, it is more accurate because of its spatial smoothing effects discussed in Section 4. Several approaches are proposed for regional forecasting.

Linear up-scaling in *Previento* is used for the regional forecasting in [36]. The ratio between the fluctuation of the wind power output of the measured single site and the ensemble of the sites is used for up-scaling. It shows how this method works practically in Germany.

In [97], the aggregated forecasting method using the distances between wind speed forecasts for a set of selected coordinates to calculate wind power forecasts in a region is proposed. Once the distance is obtained, the wind power forecast is calculated by comparing the new wind speed forecast with the stored historical wind speed forecasts and their corresponding total wind power measured in the region. The accuracy of the proposed method is verified by comparing the results with the reference method.

In [98], an ANN–Fuzzy approach based on the up-scaling approach is used to forecast the regional wind generation. Three different approaches are introduced based on how much the NWPs and on-line SCADA data are available: FNN up-scaling, Cascaded model, and FNN cluster model. The results show that the overall performance is improved but it is difficult to beat the persistence model for the first look-ahead time. SCADA data is necessary to enhance the performance in the first forecast horizon.

A finite state Markov Chain model is developed to forecast the aggregated power output from a wind farm in [99]. The model takes into account both the spatial and temporal dynamics of wind power output. For spatial dynamics, a rigorous step-by-step procedure to characterize the probability distribution of the aggregated power output is presented. The temporal dynamics is characterized using auto-regression analysis tools.

The models of regional forecasting are mostly based on the up-scaling approach. It is difficult to obtain the wind power measurements and NWPs from all the wind farms in a region. Therefore, the up-scaling approach is used to scale the available on-line measurements and NWPs up to the region. There is not much work reported dealing with regional forecasting. When wind energy penetration increases significantly good solutions to regional forecasting will be needed.

2.4. *Probabilistic forecasting*

The forecasting models discussed so far provide the point forecast for how much wind speed and power can be expected for a number of hours into the future. It is important to know not

only the point forecast but also its expected uncertainty. Knowing the uncertainty of the forecast enables the system operator to assess the risk of the point forecast. Different approaches can be found in the literature regarding the problem of probabilistic forecast. In this section, some of the representative methods are discussed.

2.4.1. Parametric approach

If there is any underlying assumption on the distribution one tries to model for the forecasting error, it is a parametric approach.

A Beta Probability Density Function (PDF) is used to model a PDF of the wind power forecast for the persistence model in [100]. First, the forecast results are divided into power classes or bins for modeling the distribution of power with the Beta PDF. The overall forecast error PDF is obtained from adding up the calculated error PDFs of all bins. The results show the usefulness of the proposed forecast error PDF for finding the optimal storage size.

The Cauchy distribution is proposed as a model distribution for the forecast error for the persistence model in [101]. The shape of the distribution is found to change significantly with the forecasting horizon. The effect of the proposed wind power forecast uncertainty is illustrated.

There is little literature available on the parametric approach due to the difficulty of defining the stochastic nature of wind speed.

2.4.2. Non-parametric approach

Contrary to the parametric approach, the non-parametric approach does not rely on any assumption about the distribution.

A non-parametric approach based on kernel density estimation is proposed to provide the complete wind power forecast distribution in [102]. The distribution of wind power is decomposed into a continuous part corresponding to all occurrences of wind speed having zero production and a discrete part corresponding to the discrete probabilities of all production values. The method levels with the references while being fast and producing the complete PDF.

The kernel density estimation is expanded to a time-adaptive model and to adopt different kernels for several types of variables in [103]. The kernel density estimation model based on the Nadaraya–Watson estimator is proposed to estimate the uncertainty in short-term wind power forecasts. It includes the adoption of specific kernels for the explanatory variables and the development of a time adaptive model. It confirms its value from testing with real data from two large wind farms in the U.S. and shows better results based on the evaluation criteria in [104]. Furthermore, kernel density estimation based on the time-adaptive quantile-copula estimator is presented in [105].

In [106], the generic methodology for assessing the forecast risk is presented. First, confidence intervals based on the resampling approach are calculated by considering the forecast horizon, the power class and the cut-off risk. Furthermore, the Meteorological Risk Index (MRI) evaluating the weather stability is used to tune the confidence intervals. The proposed method is generic and can be applied to any wind forecasting models. However, it does not seem to have very much influence on the quantile estimation in [107]. The most influential variable is the forecasted wind power production. Furthermore, the results show increased uncertainty for westerly winds. Also, the effect of the horizon on the quantiles is minor.

Probabilistic wind power forecasts using Local Quantile Regression (LQR) is proposed in [108]. This approach does not require the distribution assumption and is easy to include more predictive information. The simulation results demonstrate its effectiveness.

In [109], a probabilistic forecasting method based on the Markov Chain model is proposed. This provides not only the estimates of future wind power generation but also the associated probability distributions. First Order Markov Chain (FOMC) and Second Order MC (SOMC) are considered. The proposed models are compared with the persistence model to evaluate forecast errors.

In [110], the proposed probabilistic model is designed to forecast eight quantiles of the wind power distribution using multiple Radial Basis Function Neural Networks (RBFNNs). The main idea is to exploit all information influencing the forecasting errors in order to estimate the wind power density function. The three uncertainties considered are the weather stability, the structure of the forecasting model, and the NWP accuracy. The developed RBFNNs are trained with the Ordinary Orthogonal Least Square (OLS) algorithm and their performance is improved using a Particle Swarm Optimization (PSO) algorithm. The simulation results show that the proposed method performs well in different weather conditions and different terrains.

In [111], the sparse Warped Gaussian Process (WGP) model is formulated to provide short-term probability forecasts of the wind power generation. It converts a non-Gaussian wind power series to a latent series, which is well modeled by a Gaussian process. Furthermore, a sparsification method is employed to reduce the computational costs of the model. The simulation results validate the effectiveness of the proposed model.

Non-parametric approaches are used when it is not possible to formulate the distribution of the forecast errors. This distribution-free approach is appealing since it is difficult to define the stochastic nature of wind. Furthermore, the wind speed and power forecast are very different depending on the forecast time horizon and location. Non-parametric approaches can be applied in this case, and as a result are suitable to estimate the uncertainty of the wind speed and power forecast.

2.4.3. Using ensemble forecast

Ensemble forecasting methods are designed to take advantage of ensemble NWPs. The ensemble NWPs are obtained by running differently calibrated NWP models or by slightly varying the initial conditions, in order to obtain a set of different forecasts [112]. Different types of meteorological ensemble forecasts are provided either by the European Centre for Medium-range Weather Forecasts (ECMWF) or the National Centre for Environmental Prediction (NCEP). A MultiScheme Ensemble Prediction System (MS-EPS) is introduced to utilize the ensemble NWPs for short-term wind power forecasting [113].

In [114], skill forecasting based on ensemble forecasts of wind power production is introduced to estimate the expected level of forecast uncertainty. Prediction risk indices based on the dispersion of wind power ensembles over a single forecast horizon or over a set of successive look-ahead times are introduced. Then, these indices are used to forecast the distribution of expected forecast errors as skill forecasts. The simulation results show that the proposed skill forecasting can provide useful information on the expected level of forecast uncertainty.

The wind power density forecasts using the calibrated and smoothed ensemble forecast are proposed in [115]. The systematic bias of the ensemble forecasts is corrected by the calibration approach that also incorporates kernel smoothing, with parameters optimized using maximum likelihood. The proposed power density forecasts provide more accurate results for wind power density and point forecasting than the reference.

The ensemble forecasts give a much better idea of what weather events may occur in the future. By comparing different forecasts, it identifies the expected spread of weather conditions

and assesses the probability of particular weather events. When the forecasts vary significantly there is a lot of uncertainty. However, if forecasts are very similar, then more confidence can be placed in the forecasts. The ensemble forecast is useful in both wind speed and power forecasting.

2.4.4. Additional models

In [116], the relation between typical weather situations and the corresponding wind speed forecast error is investigated to model the uncertainty of the forecast. First, the Cluster analysis using the Principal Component Analysis (PCA) rather than complex meteorological information is used to group days with similar meteorological conditions into classes. Then, for each of these groups the forecast error is determined separately. It is found that different meteorological situations have significant differences in the forecasting error.

In [117], it is necessary to assess both temporal and spatial interdependences in order to evaluate the aggregate error for the regional uncertainty estimates. In this manner, the spatial modeling of the wind power forecast uncertainty is proposed, which is important for the optimal management of power flows in the large region. The improvement of the probabilistic forecasting is discussed.

The spatio-temporal modeling of wind power forecast uncertainty considering the interdependence of both time and space is proposed in [118]. It is shown that there is significant cross-correlation between forecast errors obtained from neighboring areas with lags of a few hours. These cross-correlation patterns characterized by wind speed and direction show that a higher prevailing wind results in a stronger dependency on remote places; while a lower prevailing wind results in a stronger dependency on local places. A further study is needed for the generalization by the methodology.

In [119], the uncertainty of wind power forecasting regarding the meteorological situation is investigated. From the simulation results, the uncertainty of wind speed forecasts is not dependent on the magnitude of the wind speed forecast. Furthermore, the uncertainty is larger for low pressure situations than high pressure situations. However, some sites do not show these differences.

A framework for evaluating the quality of probabilistic forecasting of wind power is presented in [104]. The framework is composed of measures and diagrams, with the aim of providing useful information on each of the properties including reliability, sharpness and resolution, and a unique skill score. The framework is applied for comparing the quality of two non-parametric methods; adaptive quantile regression and adapted re-sampling. The relevance and interest of the proposed framework are discussed.

In [120], a methodology for using the variability in wind speed forecasts at multiple grid points in NWP systems is presented to forecast the uncertainty in future wind power generation. The basic concept is that a major source of uncertainty in NWP forecasts arises from potential misplacement of weather features. The comparison between the proposed method and NWP ensembles is performed. It demonstrates good accuracy in forecasting large forecast errors.

A wide comparison is carried out between the ARMA models, five kinds of ANN models, and Adaptive Network based Fuzzy Inference System (ANFIS) models in [121]. The comparison looks at many forecasting methods, time horizons and a performance analysis. A further analysis of the statistical distribution of normalized errors from the forecasting models is performed.

2.5. Offshore forecasting

Nowadays, offshore wind has a lot of attention and is expected to be installed more in the future because of more frequent and powerful winds. However, the offshore wind forecasting is still in the early phases of the development. There are not many available specific forecasting models for offshore in the literature. Further advances in offshore forecasting will help offshore wind penetration levels.

Most forecasting models have been designed for onshore. For the physical approach to offshore forecasting, the special meteorological characteristic of the marine atmospheric boundary layer has to be considered including the stability of the boundary layer, wind–wave interaction, etc., [122]. However, the statistical approach does not need to consider the precise offshore conditions. Results from various offshore forecasting methods are investigated in [123].

In [124], the evaluation of NWPs forecasts for offshore sites is performed. Then, for the physical forecasting approach, the special meteorological characteristics of the marine boundary layer are considered to calculate the wind speed at the hub height of the wind turbines by using the derived vertical wind profile. The effectiveness of the proposed method is demonstrated by comparing with measurements.

In [61,114,125,126], some of the statistical approaches use offshore data as an input, but the specific technique for dealing with offshore data is not discussed.

3. Accuracy of wind speed and power forecasting

3.1. Reference models

A number of reference models have been introduced as benchmark models. These models may be used for initial testing of the accuracy of new approaches to wind forecasting. A number of existing reference models are reviewed in this section.

3.1.1. Persistence model

The persistence model is a commonly used benchmark model. In this model the future wind power will be the same as occurred in the present time step as given by

$$\hat{P}_{t+k|t} = P_t \tag{2}$$

where $\hat{P}_{t+k|t}$ is the forecast at time t for the look ahead time k and P_t is the measurement at time t. This model performs well for short forecasting horizons.

3.1.2. Weighted sum between persistence and the mean power production

The persistence model performs well for the short-term forecast. However, it is not reasonable to use the persistence model when the forecast time horizon is more than a few hours. For this case, a new reference model has been proposed [127]. It is a weighted sum between the persistence and the mean given as

$$\hat{P}_{t+k|t} = a_k P_t + (1-a_k)\overline{P} \tag{3}$$

where P_t is the measurement at time t, $\overline{P}$ is the estimated mean, and a_k is the correlation coefficient between P_t and P_{t+k} defined as

$$a_k = \frac{(1/N)\sum_{t=1}^{N-k}\tilde{P}_t\tilde{P}_{t+k}}{(1/N)\sum_{t=1}^{N-k}\tilde{P}_t^2} \tag{4}$$

where

$$\tilde{P}_t = P_t - \overline{P} \tag{5}$$

3.1.3. OL-Persistence model

For regional forecasting, total regional power is seldom available. Therefore, the On-Line (OL) Persistence model is introduced

for the regional forecasting as a benchmark model [32]. This model is the sum of the production of the representative wind farms with measurements, scaled to the total wind power and is given as

$$\hat{P}^{reg}_{t+k|t} = \frac{P^{reg}_{inst}}{\sum_{i=1}^{M_r} P^{wf}_{inst,i}} \sum_{i=1}^{M_r} P^{wf}_{i,t} \tag{6}$$

where P^{reg}_{inst} is the total installed capacity in the region, $P^{wf}_{inst,i}$ is the installed capacity of the M_r wind farms for which on-line measures are available, and $P^{wf}_{i,t}$ is the power measured at those wind farms at time t.

3.2. Model performance evaluation

To determine the model performance in terms of the forecasting accuracy, several model accuracy measures are discussed in this section.

The *forecast error* is the difference between the measurement and the forecast and is given as

$$e_{t+k|t} = P_{t+k} - \hat{P}_{t+k|t} \tag{7}$$

Sometimes, the *normalized forecast error* is used. The forecast error is normalized by the installed capacity (P_{inst}) as

$$\varepsilon_{t+k|t} = \frac{1}{P_{inst}} e_{t+k|t} \tag{8}$$

To assess the quality of the forecast, several evaluation criteria are used; *Bias*, Mean Absolute Error (*MAE*), Mean Absolute Percentage Error (*MAPE*), Mean Square Error (*MSE*), Root Mean Square Error (*RMSE*), and Standard Deviation of Errors (*SDE*) [128,129], as given by

$$Bias_k = Avg(e_{t+k|t}) = \bar{e}_k = \frac{1}{N}\sum_{t=1}^{N} e_{t+k|t} \tag{9}$$

$$MAE_k = \frac{1}{N}\sum_{t=1}^{N} |e_{t+k|t}| \tag{10}$$

$$MAPE_k = \frac{1}{N}\sum_{t=1}^{N} \left|\frac{e_{t+k|t}}{P_{t+k}}\right| \tag{11}$$

$$MSE_k = \frac{1}{N}\sum_{t=1}^{N} (e_{t+k|t})^2 \tag{12}$$

$$RMSE_k = \sqrt{MSE_k} = \sqrt{\frac{1}{N}\sum_{t=1}^{N} (e_{t+k|t})^2} \tag{13}$$

$$SDE_k = Std(e_{t+k|t}) = \sqrt{\frac{1}{N}\sum_{t=1}^{N} (e_{t+k|t} - \bar{e}_k)^2} \tag{14}$$

where N is the total number of samples, and $Avg(\cdot)$ and $Std(\cdot)$ denote the average and the standard deviation respectively. Furthermore, the $RMSE_k$ can be expressed by the combination between $Bias_k$ and the SDE_k as

$$RMSE_k^2 = Bias_k^2 + SDE_k^2 \tag{15}$$

In the model comparison, it is important to quantify the improvements of the advanced model over the benchmark model. In this manner, the improvement with respect to the reference model is introduced as [128,129]

$$\mathrm{Imp}_{EC,k} = \frac{EC_{ref,k} - EC_{adv,k}}{EC_{ref,k}} \tag{16}$$

where EC stands for the evaluation criteria such as *MAE*, *RMSE*, *SDE*, etc.

3.3. Forecast accuracy

Using the advanced forecasting models introduced in Section 2, it is possible to provide better forecasts of wind speed and power than the reference models. However, it is very difficult to say which model is the best because of its site dependency. Although the forecasting model performs well, it does not guarantee that the model works well at another site. Therefore, how the general forecast accuracy varies is discussed in this section.

3.3.1. The accuracy by forecast time horizon

The forecast accuracy decreases when prediction length increases. The MAE of short-term forecasts is typically in the range of 5–15% and then the errors increase rapidly with an increase in the forecast time horizon. Thus, the MAE is typically in the range of 13–21% range for 1–2 days ahead and rises to 20–25% range after about 3 days [10].

3.3.2. The accuracy by location complexity

In [79], the average value of the normalized MAE (NMAE) for the 12 h forecast horizon is compared based on the terrain complexity of the wind farm. Much smaller NAME values in a flat terrain wind farm (low complexity location) are observed than in complex terrains (high complexity location). There is a significant increase of the NMAE value when the terrain complexity is increased. Furthermore, offshore wind farms have slightly higher NMAE values relative to the flat terrain wind farm.

3.3.3. The accuracy by seasonal variability

In [130], the performance of the forecasting models is related to the seasonal variability. Smaller forecasting errors are observed in winter than summer because of the higher level of wind speeds and the larger uncertainty in the summer stormy weather situations, in particular low pressure systems with fast moving frontal zones containing complicated wind patterns.

3.3.4. The accuracy by weather condition

In [106], the forecasting error is compared as a function of the Meteorological Risk Index (MRI) evaluating the weather stability. The forecasting error increases linearly when MRI increases (the higher MRI represents unstable weather regimes). Furthermore, in [119], the forecasting uncertainty does not depend on the wind speed but on the pressure. The forecasting error in the low pressure situation is larger than the high pressure situation. These patterns are also observed in [116].

4. Improvement in forecasting performance

Development activities are on-going in reducing the forecasting error in wind speed and power forecasting, spatial correlation forecasting, regional forecasting, probabilistic forecasting, and offshore forecasting. In this section, some of the potential options to help improve the forecasting accuracy are discussed.

4.1. Kalman filtering

It is well known that the accuracy of NWPs has a major impact on the forecasting of wind speed and power. Therefore, reducing the uncertainty of NWPs can lead to significant forecasting improvements. To improve the accuracy of NWPs, the Kalman filtering algorithm is applied to filter out systematic errors. The Kalman filtering algorithm provides the statistically optimal estimate recursively by combining recent weighted observations which minimize the corresponding biases.

In [131], the improvements in wind speed forecasting with the application of the Kalman filtering are investigated. Third-order polynomial functions are implemented in the Kalman filtering algorithm. For the evaluation, two NWP models having different characteristics and horizontal resolutions are tested. The simulation results show that the forecasting accuracy is significantly improved by using the filtered NWPs. The significant forecast improvement using the Kalman filtering can be also found in [59,132,133].

4.2. Optimal combination

The combination of different NWPs or forecasting models takes advantage from each model. The advantage of combining the models, of course, improves the forecast accuracy. Furthermore, the combination can reduce the risk from extreme events. The combination of forecasting methods is discussed in Section 2, and the optimal combination can significantly reduce forecast error. Here, the optimal combination of NWPs is discussed.

In [134,135], a classification scheme is used to find optimal combinations for specific weather situations. The different NWP models are exploited by applying the optimal weights depending on the prevailing weather conditions. It shows that the optimal combination of NWPs significantly outperforms others even if the single NWP is already very well optimized. The combination of different NWPs is performed based on the quality of individual forecasts in [125,136].

In [137], the combination between measured data and multiple wind forecasting models is proposed by advanced machine learning techniques. The input sources are the wind forecasts profiles, derived by synoptic and local atmospheric models, and the actual climatic variable evolution measured by local environmental stations. The simulation results demonstrate the effectiveness of the proposed data fusion algorithms.

4.3. Spatial smoothing effects

Under operational conditions, regional forecasting is required for the system operator to estimate the total wind power production. The fluctuations of the combined power output of distributed wind farms are damped, which results in decrease in fluctuations of the regional power output compared to the forecast for single sites. This is called spatial smoothing effects. These effects provide the motivation for developing regional forecasting models rather than calculating the sum of the wind power forecast from single sites. Several forecasting models are discussed in Section 2.3. The reduction of the forecast error is found in the literature [138,139].

4.4. Statistical downscaling

NWPs are primary inputs to forecasting models. So improving NWPs can help to improve wind speed and power forecasting. NWPs are only available for grid points which generally correspond to areas that are larger than the wind farms themselves. Therefore, estimating the wind speed at the wind farm location can provide more accurate wind speed forecast as an input to the forecasting models. The basic idea of statistical downscaling is to use higher resolution calculations by adding more complete physics descriptions to capture more precise local conditions. The analysis results show that wind power forecasting using the statistical down scaled NWPs can improve the performance [140–142]. Furthermore, some of the advanced NWP models are examined in [143–145].

4.5. Input parameter selection

The selection of the input parameters for the forecasting model is crucial to the performance of the forecasts. Several input parameters are investigated in the literature for the purpose of reducing the forecasting error.

In [146], the inclusion of off-site observations with NWP models can increase the forecast accuracy. Despite the inherent large forecast error from NWPs, adding off-site observations leads to increases in forecast accuracy. Furthermore, as the number of reference stations providing the measurements increase, the forecasting errors tend to decrease [96]. The improvements by the off-site observations can be the motivation for developing spatial correlation forecasting which forecasts wind speed and power at target sites by using the observations from neighboring measuring stations, as described in Section 2.2.

Several meteorological parameters as inputs have been considered for improving the performance of the forecast. The inclusion of wind direction with wind speed can reduce the forecasting error [96,116,118,126]. Sometimes the wind vector applying both wind speed and direction is used [45,52,69]. Besides the obvious importance of the wind speed as an input parameter, temperature and pressure can help improve forecasts [69,116,147].

In [148], the inclusion of the wind speed forecast at wind turbine hub height shows significant improvements in forecast accuracy.

Furthermore, transformed data rather than wind speed itself show potential for improving the forecast. Several transformation techniques are used: wavelet decomposition [41,42,54,55,62], empirical mode decomposition [56,57], and frequency domain approach [76].

4.6. Power curve modeling

When converting the wind speed to wind power production, inaccuracies in the non-linear relation leads to further errors. Wind power and wind speed are related through a cubic relationship. Thus, small variations in the wind speed result in much larger deviations in the wind power. The use of the certified manufacture power curves does not guarantee accurate conversions. Using an accurate relation between the wind speed and power can greatly minimize conversion errors when converting the wind speed forecast to the wind power forecast.

The conventional wind power curve model is extended to a wind farm model by the addition of the wind direction dependence with the wind speed dependence. Such a two dimensional wind farm power curve model may help to provide more accurate relations between wind speed and power [50,140,142].

Statistical techniques rather than the wind power curve may be used to describe the non-linear relation between wind speed and wind power. The polynomial regression is used to estimate the wind power by using the explanatory variables such as wind speed, direction, etc. Furthermore, non-linear hyperbolic functions containing trigonometric terms which describe the non-linear behavior are used [133]. Sometimes, advanced statistical approaches (ANN, Fuzzy logic, etc.) are used to estimate wind power from the various inputs [55]. However, such a relation does not need to be described when the wind power is forecasted directly from the raw input data. However, it is required when forecasting the wind speed and then converting it to the power.

4.7. Forecasting parameter

One of the most important decisions in a wind power system is choosing which parameters will be used in the forecast. The forecaster can choose the wind speed alone or the wind speed and

direction or the wind vector as the forecasting parameters. Then, the forecasting wind information is converted to the wind power production. Or the forecaster can forecast the wind power production directly. Furthermore, the forecaster can choose regional or probabilistic forecasting. Choosing the appropriate forecasting parameters can improve the performance [149].

5. Conclusion and future works

5.1. Discussion and conclusion

Today's power system is facing growing challenges in maintaining a secure and reliable energy supply. Part of the growing challenge is the possibility of significant levels of uncertain wind generation being installed on power system. This brings new challenges involving the management of wind intermittence. Accurate forecasting of wind power is necessary to meeting these challenges.

The main objectives of wind speed and power forecasting are to estimate the wind speed and power as quickly and accurately as possible. With more accurate forecasting integration of large amounts of wind power into power system can be achieved. Accurate forecasting tools reduce the financial risk and lead to improved scheduling and unit commitment plans.

This paper provides an overview of forecasting tools that are available for wind generation. The wind speed and power forecasting approaches reviewed have different characteristics, with different approaches providing better results for different forecast time horizons and locations. This paper divides forecasting methods into five categories: wind speed and power forecasting, spatial correlation forecasting, regional forecasting, probabilistic forecasting, and offshore forecasting. An overview of existing research in each category is presented.

Several wind speed and power forecasting approaches, including physical, statistical, and combination approaches, have been implemented and are now commercially available. The statistical approaches provide good results in the majority of cases, including short-term, medium-term, and long-term forecasting. However, in the very short-term and short-term horizon, the influence of atmospheric dynamics becomes more important, so that the use of the physical approaches becomes necessary.

The statistical forecasting approaches, such as conventional statistical approaches, ANN, and ANN–Fuzzy, use large amounts of historical data as input. The conventional statistical approaches are mostly aimed at very short-term and short-term forecasting. ANN is able to model complex non-linear relationships and extract the dependence between the inputs and outputs through learning and training. Fuzzy logic outperforms others when dealing with reasoning problems, while learning and training abilities are mediocre. The merging of the ANN approach with the Fuzzy logic, creating the ANN–Fuzzy approach, provides excellent performance.

It is difficult to say which model is the best because different models perform differently in different situations. The combination approach attempts to leverage the strengths of different modeling approaches. This approach is able to not only improve the forecast accuracy, but also reduces the risk from extreme events.

In order to select a suitable location of wind generation, it is necessary to assess the wind power sufficiency of the neighboring regions. In this case, spatial correlation forecasting may be applied to estimate the characteristics of the wind resource at sites where insufficient information is not available. Current models use functions that describe the wind flow depending on the distance between two sites by selectively using the topography of the area, the height of the measuring mast, the cross correlation factor, or other relative meteorological data. These models are more difficult than typical time-ahead forecasting models because they require measurements from many spatially correlated sites and the associated measurement delay times.

Regional forecasting has become more important for market operators to estimate the total wind power production in a region. Furthermore, it has been shown that regional forecasts provide faster and more accurate results than single farm forecasts because of the spatial smoothing effects. However, few studies have looked into the particularities of regional forecasting. When wind energy penetration increases significantly solutions to this problem will be needed.

Probabilistic forecasting gives an estimate of where the wind production will lie within a certain degree of confidence. In this review some of the representative methods are considered, including the parametric approach, non-parametric approach, and ensemble forecast. There are not many parametric approaches available due to the complex stochastic nature of wind speed. Thus, non-parametric approaches, and distribution-free approaches, have been more appealing. In addition, ensemble forecasting models for probabilistic forecasting are used in order to obtain the expected spread of weather conditions and assess the probability of particular weather events.

In future, major wind power developments are expected to be installed offshore. More frequent and powerful wind speeds represent the main advantages of offshore power production. However, offshore wind forecasting is in an early phase of development. All state-of-the-art forecasting models were originally designed for onshore. For physical forecasting approaches special modeling considerations have to be considered for offshore. However, with statistical approaches precise knowledge of offshore conditions is not needed.

Using advanced wind speed and power forecasting approaches introduced in Section 2, it is possible to provide significantly better forecasts than the simplistic or reference forecasting approaches. However, it is difficult to say which model is the best because wind speed and power forecasting is not “plug-in-play” due to the site-dependence. Therefore, an evaluation of accuracy relative to the forecasting model performance is discussed. The general forecasting accuracy is then considered along with the level of forecasting errors that can be expected depending on the forecast time horizon, location complexity, seasonal variability, and weather conditions. The forecasting accuracy goes down with increasing forecast time horizon, terrain complexity, and unstable weather regimes.

Finally, several potential techniques for improving the accuracy of the models are discussed: (1) Kalman filtering of systematic errors coming from NWPs. (2) The combination of different NWPs or forecasting models. (3) Combining power outputs of distributed wind farms providing spatial smoothing effects. (4) Estimating the wind speed at wind farm locations by statistical down scaling. (5) Appropriate selection of input parameters. (6) Improved power curve modeling. (7) Choosing the appropriate forecasting parameters.

5.2. Future work

The reviewed wind speed and power forecasting approaches in this paper provide a foundation for future research. Future work to be considered includes the following:

- Further improvements in both physical and statistical forecasting approaches and improved approaches for the combination of different forecasting approaches can be expected to further reduce forecasting errors.

- Extending the forecasts further into the future, enabling long-term planning.
- Regional forecasting is useful in feasibility studies of prospective installations and assessment of the potential impact on system reliability. The choice of reference sites and their combinations should be considered in regional forecasting.
- Forecasting the aggregated wind power on a regional basis would be useful for management of total wind power production. It would also be useful to detect extreme events so that market operators can manage trading as wind power ramps up and down.
- Probabilistic forecasting could provide probability distributions of the forecasting errors, providing the opportunity to reduce the reserve capacity for balancing wind power forecast errors.
- The development of operational ensemble forecasts using the data from several NWPs would help improve the forecast accuracy.
- Improved offshore forecasting models are needed to improve the offshore forecasts that are currently being done with models developed for onshore.
- New approaches for complex terrains are required. These approaches could incorporate higher resolution maps.
- Improving and tuning the NWP model to predict the hub-height wind would help improve the forecasting accuracy. It is sometimes required to forecast accurate pressure, temperature, and other related weather parameters.
- Additional use of online wind measurement data has the potential for improved forecasts, especially for very short-term and short-term wind power forecasting.
- Further research on automatic adaptive parameter estimation is required since wind speed and power forecasting is very site-dependent.
- Increasing the spatial and time resolution of NWPs, better taking into account local phenomena, would help to improve the forecast.
- Forecasting extreme events, as opposed to common behavior, would be very valuable to protecting the power system.

Acknowledgment

The authors would like to thank Electrical Distribution Design, Inc., for funding and providing technical assistance for this study.

Reference

[1] United States Department of Energy. 20% Wind energy by 2030; 2008.

[2] Lei M, Shiyan L, Chuanwen J, Hongling L, Yan Z. A review on the forecasting of wind speed and generated power. Renew Sustain Energy Rev 2009;13:915–20.

[3] Foley AM, Leahy PG, Marvuglia A, McKeogh EJ. Current methods and advances in forecasting of wind power generation. Renew Energy 2012;37:1–8.

[4] Cutler N. Wind energy forecasting issues paper. Centre for Energy and Environmental Markets, The University of New South Wales; 2006.

[5] Dongmei Z, Yuchen Z, Xu Z. Research on wind power forecasting in wind farms. In: Proceedings of the 2011 IEEE power engineering and automation conference (PEAM); 2011. p. 175–8.

[6] Foley AM, Leahy PG, McKeogh EJ. Wind power forecasting & prediction methods. In: Proceedings of the 9th international conference on environment and electrical engineering (EEEIC); 2010. p. 61–4.

[7] Kariniotakis G, Pinson P, Siebert N, Giebel G, Barthelmie R. The state of the art in short-term prediction of wind power – from an offshore perspective. 2004 Sea Tech Week; 2004.

[8] Costa A, Crespo A, Navarro J, Lizcano G, Madsen H, Feitosa E. A review on the young history of the wind power short-term prediction. Renew Sustain Energy Rev 2008;12:1725–44.

[9] Negnevitsky M, Mandal P, Srivastava AK. An overview of forecasting problems and techniques in power systems. In: Proceedings of the 2009 IEEE power and energy society general meeting; 2009. p. 1–4.

[10] Zack J. Overview of wind energy generation forecasting. Albany, NY: TrueWind Solutions, LLC. & AWS Scientific, Inc.; 2003.

[11] Soman SS, Zareipour H, Malik O, Mandal P. A review of wind power and wind speed forecasting methods with different time horizons. In: Proceedings of the 2010 north american power symposium (NAPS); 2010. p. 1–8.

[12] Colak I, Sagiroglu S, Yesilbudak M. Data mining and wind power prediction: a literature review. Renew Energy 2012;46:241–7.

[13] Bhaskar M, Jain A, Venkata Srinath N. Wind speed forecasting: present status. In: Proceedings of the 2010 international conference on power system technology (POWERCON); 2010. p. 1–6.

[14] Tsikalakis AG, Hatziargyriou ND, Katsigiannis YA, Georgilakis PS. Impact of wind power forecasting error bias on the economic operation of autonomous power systems. Wind Energy 2009;12:315–31.

[15] Kennedy J, Fox B, Morrow DJ. Distributed generation as a balancing resource for wind generation. Renew Power Gener, IET 2007;1:167–74.

[16] Marti I, San Isidro MJ, Gaston M, Loureiro Y, Sanz J, Perez I. Economic impact of wind power forecast. In: Proceedings of the 2004 european wind energy conference and exhibition; 2004.

[17] Milligan MR, Miller AH, Chapman F. Estimating the economic value of wind forecasting to utilities. Golden, Colorado: National Renewable Energy Laboratory; 1995.

[18] Lowery C, O′Malley M. Impact of wind forecast error statistics upon unit commitment. IEEE Trans Sustain Energy 2012;3:760–8.

[19] Mahoney WP, Parks K, Wiener G, Yubao L, Myers WL, Juanzhen S, et al. A wind power forecasting system to optimize grid integration. IEEE Trans Sustain Energy 2012;3:670–82.

[20] Usaola J, Ravelo O, González G, Soto F, Dávila MC, Díaz-Guerra B. Benefits for wind energy in electricity markets from using short term wind power prediction tools; a simulation study. Wind Eng. 2004;28:119–27.

[21] Wang J, Botterud A, Bessa R, Keko H, Carvalho L, Issicaba D, et al. Wind power forecasting uncertainty and unit commitment. Appl Energy 2011;88:4014–23.

[22] Botterud A, Wang J, Miranda V, Bessa RJ. Wind power forecasting in U.S. electricity markets. Electr J 2010;23:71–82.

[23] Smith JC, Ahlstrom ML, Zavadil RM, Sadjadpour A, Philbrick CR. The role of wind forecasting in utility system operation. In: Proceedings of the 2009 IEEE power and energy society general meeting; 2009. p. 1–5.

[24] Ernst B, Oakleaf B, Ahlstrom ML, Lange M, Moehrlen C, Lange B, et al. Predicting the wind. Power Energy Mag, IEEE 2007;5:78–89.

[25] Dica C, Dica CI, Vasiliu D, Comanescu G, Ungureanu M. Wind power short-term forecasting system. In: Proceedings of the 2009 IEEE Bucharest PowerTech; 2009. p. 1–7.

[26] Gubina AF, Keane A, Meibom P, O′Sullivan J, Goulding O, McCartan T, et al. New tool for integration of wind power forecasting into power system operation. In: Proceedings of the 2009 IEEE Bucharest PowerTech; 2009. p. 1–6.

[27] Yutong Z, Ka Wing C. The impact of wind forecasting in power system reliability. In: Proceedings of the 2008 third international conference on electric utility deregulation and restructuring and power technologies (DRPT); 2008. p. 2781–5.

[28] Ahlstrom Jones L, Zavadil R, Grant W. The future of wind forecasting and utility operations. Power Energy Mag, IEEE 2005;3:57–64.

[29] Ahlstrom ML, Zavadil RM. The role of wind forecasting in grid operations & reliability. In: Proceedings of the 2005 IEEE/PES transmission and distribution conference and exhibition: Asia and Pacific; 2005. p. 1–5.

[30] Lange M, Focken U. Physical approach to short-term wind power prediction. New York, NY: Springer; 2006.

[31] Landberg L, Giebel G, Nielsen HA, Nielsen T, Madsen H. Short-term prediction – an overview. Wind Energy 2003;6:273–80.

[32] Nils S. Development of methods for regional wind power forecasting [Ph.D.]. MINES ParisTech; 2008.

[33] Landberg L. Short-term prediction of local wind conditions. J Wind Eng Ind Aerodyn 2001;89:235–45.

[34] Landberg L. Short-term prediction of the power production from wind farms. J Wind Eng Ind Aerodyn 1999;80:207–20.

[35] Landberg L. A mathematical look at a physical power prediction model. Wind Energy 1998;1:23–8.

[36] Focken U, Lange M, Waldl H-P. Previento – a wind power prediction system with an innovative upscaling algorithm. In: Proceedings of the 2001 european wind energy conference & exhibition; 2001.

[37] Marti I, Cabezon D, Villanueva J, Sanisidro MJ, Loureiro Y, Cantero E, et al. LocalPred and RegioPred. Advanced tools for wind energy prediction in complex terrain. In: Proceedings of the 2003 european wind energy conference & exhibition; 2003.

[38] McGowin C. California wind energy forecasting system development and testing. Phase 1: Initial testing. Palo Alto, California: Electric Power Research Institute (EPRI); 2003.

[39] Milligan M, Schwartz M, Wan Y. Statistical wind power forecasting models: results for U.S. wind farms. WINDPOWER 2003; 2003.

[40] Milligan M, Schwartz MN, Wan Y. Statistical wind power forecasting for U.S. wind farms. In: Proceedings of the 17th conference on probability and statistics in the atmospheric sciences/2004 american meteorological society annual meeting; 2004.

[41] Liu H, Tian H-Q, Chen C, Li Y-f. A hybrid statistical method to predict wind speed and wind power. Renew Energy 2010;35:1857–61.

[42] Peng L, Lili Y. Short-term wind speed forecasting based on non-stationary time series analysis and ARCH model. In: Proceedings of the 2011 International Conference on Multimedia Technology (ICMT); 2011. p. 2549–53.
[43] Meng-Di W, Qi-Rong Q, Bing-Wei C. Short-term wind speed forecasting combined time series method and arch model. In: Proceedings of the 2012 international conference on machine learning and cybernetics (ICMLC); 2012. p. 924–7.
[44] Xiaodong Z, Jianwen Z, Yinping L, Rongbao Z. Short-term forecasting of wind speed based on recursive least squares. In: Proceedings of the 2011 international conference on electrical and control engineering (ICECE); 2011. p. 367–70.
[45] Erdem E, Shi J. ARMA based approaches for forecasting the tuple of wind speed and direction. Appl Energy 2011;88:1405–14.
[46] Miranda MS, Dunn RW. One-hour-ahead wind speed prediction using a Bayesian methodology. In: Proceedings of the 2006 IEEE power engineering society general meeting; 2006. p. 1–6.
[47] Kani SAP, Riahy GH. A new ANN-based methodology for very short-term wind speed prediction using Markov chain approach. In: Proceedings of the 2008 IEEE Canada electric power conference (EPEC); 2008. p. 1–6.
[48] Jursa R. Variable selection for wind power prediction using particle swarm optimization. In: Proceedings of the 9th annual conference on genetic and evolutionary computation; 2007. p. 2059–65.
[49] Amjady N, Keynia F, Zareipour H. Wind power prediction by a new forecast engine composed of modified hybrid neural network and enhanced particle swarm optimization. IEEE Trans Sustain Energy 2011;2:265–76.
[50] Amjady N, Keynia F, Zareipour H. Short-term wind power forecasting using ridgelet neural network. Electr Power Syst Res 2011;81:2099–107.
[51] Li G, Shi J. On comparing three artificial neural networks for wind speed forecasting. Appl Energy 2010;87:2313–20.
[52] Kitajima T, Yasuno T. Output prediction of wind power generation system using complex-valued neural network. In: Proceedings of the 2010 SICE annual conference; 2010. p. 3610–3.
[53] Blonbou R. Very short-term wind power forecasting with neural networks and adaptive Bayesian learning. Renew Energy 2011;36:1118–24.
[54] Catalão JPS, Pousinho HMI, Mendes VMF. Short-term wind power forecasting in Portugal by neural networks and wavelet transform. Renew Energy 2011;36:1245–51.
[55] Bhaskar K, Singh SN. AWNN-assisted wind power forecasting using feed-forward neural network. IEEE Trans Sustain Energy 2012;3:306–15.
[56] Guo Z, Zhao W, Lu H, Wang J. Multi-step forecasting for wind speed using a modified EMD-based artificial neural network model. Renew Energy 2012;37:241–9.
[57] Liu H, Chen C, Tian H-q, Li Y-f. A hybrid model for wind speed prediction using empirical mode decomposition and artificial neural networks. Renew Energy 2012;48:545–56.
[58] Celik AN, Kolhe M. Generalized feed-forward based method for wind energy prediction. Appl Energy 2013;101:582–8.
[59] Zhao P, Wang J, Xia J, Dai Y, Sheng Y, Yue J. Performance evaluation and accuracy enhancement of a day-ahead wind power forecasting system in China. Renew Energy 2012;43:234–41.
[60] Douak F, Melgani F, Benoudjit N. Kernel ridge regression with active learning for wind speed prediction. Appl Energy 2013;103:328–40.
[61] Sideratos G, Hatziargyriou ND. An advanced statistical method for wind power forecasting. IEEE Trans Power Syst 2007;22:258–65.
[62] Catala JPS, Pousinho HMI, Mendes VMF. Hybrid wavelet-PSO-ANFIS approach for short-term wind power forecasting in Portugal. IEEE Trans Sustain Energy 2011;2:50–9.
[63] Hong Y-Y, Chang H-L, Chiu C-S. Hour-ahead wind power and speed forecasting using simultaneous perturbation stochastic approximation (SPSA) algorithm and neural network with fuzzy inputs. Energy 2010;35:3870–6.
[64] Mori H, Kurata E. Application of Gaussian Process to wind speed forecasting for wind power generation. In: Proceedings of the 2008 IEEE international conference on sustainable energy technologies (ICSET); 2008. p. 956–9.
[65] Peng K, Feng G. Sparse heteroscedastic Gaussian process for shortterm wind speed forecasting. In: Proceedings of the 2012 international joint conference on neural networks (IJCNN); 2012. p. 1–8.
[66] Liu H, Shi J, Erdem E. Prediction of wind speed time series using modified Taylor Kriging method. Energy 2010;35:4870–9.
[67] Chi-Yo H, Yu-Wei L, Wei-Chang T, Po-Yen W. Short term wind speed predictions by using the grey prediction model based forecast method. In: Proceedings of the 2011 IEEE green technologies conference (IEEE-Green); 2011. p. 1–5.
[68] Shu F, Liao JR, Yokoyama R, Luonan C, Wei-Jen L. Forecasting the wind generation using a two-stage network based on meteorological information. IEEE Trans Energy Convers 2009;24:474–82.
[69] Took CC, Strbac G, Aihara K, Mandic DP. Quaternion-valued short-term joint forecasting of three-dimensional wind and atmospheric parameters. Renew Energy 2011;36:1754–60.
[70] Li G, Shi J. Application of Bayesian model averaging in modeling long-term wind speed distributions. Renew Energy 2010;35:1192–202.
[71] Jiang Y, Song Z, Kusiak A. Very short-term wind speed forecasting with Bayesian structural break model. Renew Energy 2013;50:637–47.
[72] Zhang W, Wu J, Wang J, Zhao W, Shen L. Performance analysis of four modified approaches for wind speed forecasting. Appl Energy 2012;99:324–33.
[73] Kusiak A, Haiyang Z, Zhe S. Short-term prediction of wind farm power: a data mining approach. IEEE Trans Energy Convers 2009;24:125–36.
[74] Zheng H, Kusiak A. Prediction of wind farm power ramp rates: a data-mining approach. J Sol Energy Eng 2009;131:031011–8.
[75] Kusiak A, Zheng H, Song Z. Wind farm power prediction: a data-mining approach. Wind Energy 2009;12:275–93.
[76] Jung J, Tam K-S. A frequency domain approach to characterize and analyze wind speed patterns. Appl Energy 2013;103:435–43.
[77] Hibon M, Evgeniou T. To combine or not to combine: selecting among forecasts and their combinations. Int J Forecast. 2005;21:15–24.
[78] Sánchez I. Short-term prediction of wind energy production. Int J Forecast 2006;22:43–56.
[79] Marti I, Kariniotakis G, Pinson P, Sanchez I, Nielsen TS, Madsen H., et al. Evaluation of advanced wind power forecasting models – results of the Anemos Project. In: Proceedings of the 2006 european wind energy conference and exhibition; 2006.
[80] Bouzgou H, Benoudjit N. Multiple architecture system for wind speed prediction. Appl Energy 2011;88:2463–71.
[81] Qian Z, Kin Keung L, Dongxiao N, Qiang W. Wind park power forecasting models and comparison. In: Proceedings of the 2012 fifth international joint conference on computational sciences and optimization (CSO); 2012. p. 27–31.
[82] Xiao Q, Cong J, Jun W. Online clustering for wind speed forecasting based on combination of RBF neural network and persistence method. In: Proceedings of the 2011 chinese control and decision conference (CCDC); 2011. p. 2798–802.
[83] Shi J, Guo J, Zheng S. Evaluation of hybrid forecasting approaches for wind speed and power generation time series. Renew Sustain Energy Rev 2012;16:3471–80.
[84] Cadenas E, Rivera W. Wind speed forecasting in three different regions of Mexico, using a hybrid ARIMA–ANN model. Renew Energy 2010;35:2732–8.
[85] Liu H, Tian H-q, Li Y-f. Comparison of two new ARIMA–ANN and ARIMA–Kalman hybrid methods for wind speed prediction. Appl Energy 2012;98:415–24.
[86] Li G, Shi J, Zhou J. Bayesian adaptive combination of short-term wind speed forecasts from neural network models. Renew Energy 2011;36:352–9.
[87] Haque AU, Mandal P, Kaye ME, Meng J, Chang L, Senjyu T. A new strategy for predicting short-term wind speed using soft computing models. Renew Sustain Energy Rev 2012;16:4563–73.
[88] Guo Z, Zhao J, Zhang W, Wang J. A corrected hybrid approach for wind speed prediction in Hexi Corridor of China. Energy 2011;36:1668–79.
[89] Thogersen ML, Motta M, Sorensen T, Nielsen P. Measure-correlate-predict methods: case studies and software implementation. In: Proceedings of the 2007 EWEA conference; 2007.
[90] Kwon S-D. Uncertainty analysis of wind energy potential assessment. Appl Energy 2010;87:856–65.
[91] Miranda MS, Dunn RW, Li F, Shaddick G, Bell KRW. Bayesian inferencing for wind resource characterisation. In: Proceedings of the 2006 international conference on probabilistic methods applied to power systems (PMAPS); 2006. p. 1–6.
[92] Alexiadis MC, Dokopoulos PS, Sahsamanoglou HS. Wind speed and power forecasting based on spatial correlation models. IEEE Trans Energy Convers 1999;14:836–42.
[93] Bechrakis DA, Sparis PD. Correlation of wind speed between neighboring measuring stations. IEEE Trans Energy Convers 2004;19:400–6.
[94] Damousis IG, Alexiadis MC, Theocharis JB, Dokopoulos PS. A fuzzy model for wind speed prediction and power generation in wind parks using spatial correlation. IEEE Trans Energy Convers 2004;19:352–61.
[95] Barbounis TG, Theocharis JB, Alexiadis MC, Dokopoulos PS. Long-term wind speed and power forecasting using local recurrent neural network models. IEEE Trans Energy Convers 2006;21:273–84.
[96] Velázquez S, Carta JA, Matías JM. Influence of the input layer signals of ANNs on wind power estimation for a target site: a case study. Renew Sustain Energy Rev 2011;15:1556–66.
[97] Lobo MG, Sanchez I. Aggregated wind power prediction methods based on distances between weather forecasting vectors. In: Proceedings of the 2009 international conference on clean electrical power; 2009. p. 242–7.
[98] Pinson P, Siebert N, Kariniotakis G. Forecasting of regional wind generation by a dynamic fuzzy-neural networks based upscaling approach. In: Proceedings of the 2003 european wind energy conference and exhibition; 2003.
[99] Murugesan S, Junshan Z, Vittal V. Finite state Markov chain model for wind generation forecast: A data-driven spatiotemporal approach. In: Proceedings of the 2012 IEEE PES innovative smart grid technologies (ISGT); 2012. p. 1–8.
[100] Bludszuweit H, Dominguez-Navarro JA, Llombart A. Statistical analysis of wind power forecast error. IEEE Trans Power Syst 2008;23:983–91.
[101] Hodge B, Milligan M. Wind power forecasting error distributions over multiple timescales. In: Proceedings of the 2011 IEEE power and energy society general meeting; 2011. p. 1–8.
[102] Juban J, Siebert N, Kariniotakis GN. Probabilistic short-term wind power forecasting for the optimal management of wind generation. In: Proceedings of the 2007 IEEE Lausanne PowerTech; 2007. p. 683–8.
[103] Bessa RJ, Miranda V, Botterud A, Jianhui W, Constantinescu EM. Time adaptive conditional kernel density estimation for wind power forecasting. IEEE Trans Sustain Energy 2012;3:660–9.

[104] Pinson P, Nielsen HA, Møller JK, Madsen H, Kariniotakis GN. Non-parametric probabilistic forecasts of wind power: required properties and evaluation. Wind Energy 2007;10:497–516.
[105] Bessa RJ, Miranda V, Botterud A, Zhou Z, Wang J. Time-adaptive quantile-copula for wind power probabilistic forecasting. Renew Energy 2012;40:29–39.
[106] Pinson P, Kariniotakis G. On-line assessment of prediction risk for wind power production forecasts. Wind Energy 2004;7:119–32.
[107] Nielsen HA, Madsen H, Nielsen TS. Using quantile regression to extend an existing wind power forecasting system with probabilistic forecasts. Wind Energy 2006;9:95–108.
[108] Bremnes JB. Probabilistic wind power forecasts using local quantile regression. Wind Energy 2004;7:47–54.
[109] Carpinone A, Langella R, Testa A, Giorgio M. Very short-term probabilistic wind power forecasting based on Markov chain models. In: Proceedings of the 2010 IEEE 11th international conference on probabilistic methods applied to power systems (PMAPS); 2010. p. 107–12.
[110] Sideratos G, Hatziargyriou ND. Probabilistic wind power forecasting using radial basis function neural networks. IEEE Trans Power Syst 2012;27:1788–96.
[111] Peng K, Feng G, Xiaohong G, Jiang W. Prediction intervals for wind power forecasting: using sparse warped Gaussian process. In: Proceedings of the 2012 IEEE power and energy society general meeting; 2012. p. 1–8.
[112] Giebel G, Landberg L, Badger J, Sattler K, Feddersen H, Nielsen TS, et al. Using ensemble forecasting for wind power. In: Proceedings of the 2003 european wind energy conference and exhibition; 2003.
[113] Lang S, Mohrlen C, Jorgensen J, Gallachoir BO, McKeogh E. Application of a multi-scheme ensemble prediction system for wind power forecasting in ireland and comparison with validation results from Denmark and Germany. In: Proceedings of the 2006 european wind energy conference and exhibition; 2006.
[114] Pinson P, Nielsen HA, Madsen H, Kariniotakis G. Skill forecasting from ensemble predictions of wind power. Appl Energy 2009;86:1326–34.
[115] Taylor JW, McSharry PE, Buizza R. Wind power density forecasting using ensemble predictions and time series models. IEEE Trans Energy Convers 2009;24:775–82.
[116] Lange M, Heinemann D. Relating the uncertainty of short-term wind speed predictions to meteorological situations. In: Proceedings of the 2003 european wind energy conference and exhibition; 2003.
[117] Papaefthymiou G, Pinson P. Modeling of spatial dependence in wind power forecast uncertainty. In: Proceedings of the 2008 10th international conference on probabilistic methods applied to power systems (PMAPS); 2008. p. 1–9.
[118] Tastu J, Pinson P, Kotwa E, Madsen H, Nielsen HA. Spatio-temporal analysis and modeling of short-term wind power forecast errors. Wind Energy 2011;14:43–60.
[119] Lange M, Heinemann D. Accuracy of short term wind power predictions depending on meteorological conditions. In: Proceedings of the 2002 global windpower conference; 2002.
[120] Cutler N, Kepert J, Outhred H, MacGill I. Characterizing wind power forecast uncertainty with numerical weather prediction spatial fields. Wind Eng 2008;32:509–24.
[121] De Giorgi MG, Ficarella A, Tarantino M. Error analysis of short term wind power prediction models. Appl Energy 2011;88:1298–311.
[122] Kariniotakis G, Mayer D, Moussafir J, Chevallaz-Perrier R, Usaola J, Sanchez I, et al. ANEMOS: development of a next generation wind power forecasting system for the large-scale integration of onshore & offshore wind farms. In: Proceedings of the 2003 european wind energy conference and exhibition; 2003.
[123] Tambke J, von Bremen L, Barthelmie R, Palomares AM, Ranchin T, Juban J, et al. Short-term forecasting of offshore wind farm production – developments of the Anemos Project. In: Proceedings of the 2006 european wind energy conference and exhibition; 2006.
[124] Tambke J, Lange M, Focken U, Wolff J-O, Bye JAT. Forecasting offshore wind speeds above the North Sea. Wind Energy 2005;8:3–16.
[125] von Bremen L. Optimal Linkage of NWP models with neural networks for offshore wind power predictions. In: Proceedings of the 6th international workshop large-scale integration of wind power and transmission networks for offshore wind farms; 2006.
[126] Gallego C, Pinson P, Madsen H, Costa A, Cuerva A. Influence of local wind speed and direction on wind power dynamics – application to offshore very short-term forecasting. Appl Energy 2011;88:4087–96.
[127] Nielsen TS, Joensen A, Madsen H, Landberg L, Giebel G. A new reference for wind power forecasting. Wind Energy 1998;1:29–34.
[128] Madsen H, Kariniotakis G, Nielsen HA, Nielsen TS, Pinson PA. Protocol for standardizing the performance evaluation of short-term wind power prediction models. In: Proceedings of the global windpower 2004 conference; 2004.
[129] Madsen H, Pinson P, Kariniotakis G, Nielsen HA, Nielsen T. Standardizing the performance evaluation of shortterm wind power prediction models. Wind Eng 2005;29:475–89.
[130] Lange M, Focken U. State-of-the-art in wind power prediction in Germany and international developments. In: Proceedings of the second workshop of international feed-in cooperation; 2005.
[131] Louka P, Galanis G, Siebert N, Kariniotakis G, Katsafados P, Pytharoulis I, et al. Improvements in wind speed forecasts for wind power prediction purposes using Kalman filtering. J Wind Eng Ind Aerodyn 2008;96:2348–62.
[132] Cassola F, Burlando M. Wind speed and wind energy forecast through Kalman filtering of numerical weather prediction model output. Appl Energy 2012;99:154–66.
[133] Stathopoulos C, Kaperoni A, Galanis G, Kallos G. Wind power prediction based on numerical and statistical models. J Wind Eng Ind Aerodyn 2013;112:25–38.
[134] Lange M, Focken U. New developments in wind energy forecasting. In: Proceedings of the 2008 IEEE power and energy society general meeting – conversion and delivery of electrical energy in the 21st century; 2008. p. 1–8.
[135] Lange M, Focken U, Meyer R, Denhardt M, Ernst B, Berster F. Optimal combination of different numerical weather models for improved wind power predictions. In: Proceedings of the 6th international workshop large-scale integration of wind power and transmission networks for offshore wind farms; 2006.
[136] Lueder von B. Combination of deterministic and probabilistic meteorological models to enhance wind farm power forecasts. J Phys: Conf Ser. 2007;75:012050.
[137] Vaccaro A, Mercogliano P, Schiano P, Villacci D. An adaptive framework based on multi-model data fusion for one-day-ahead wind power forecasting. Electr Power Syst Res 2011;81:775–82.
[138] Focken U, Lange M, Mönnich K, Waldl H-P, Beyer HG, Luig A. Short-term prediction of the aggregated power output of wind farms – a statistical analysis of the reduction of the prediction error by spatial smoothing effects. J Wind Eng Ind Aerodyn 2002;90:231–46.
[139] Yu H, Liuchen C. A study of the reduction of the regional aggregated wind power forecast error by spatial smoothing effects in the Maritimes Canada. In: Proceedings of the 2010 IEEE electric power and energy conference (EPEC); 2010. p. 1–6.
[140] Kariniotakis G, Halliday J, Brownsword R, Marti I, Palomares A, Cruz I, et al. Next generation short-term forecasting of wind power – overview of the ANEMOS Project. In: Proceedings of the 2006 european wind energy conference and exhibition; 2006.
[141] Galanis G, Badger J, Marti Perez I, Louka P, Kallos G, Palomares AM, et al. Short-term forecasting using advanced physical modelling – the results of the Anemos Project. In: Proceedings of the 2006 european wind energy conference and exhibition; 2006.
[142] Nielsen TS, Madsen H, Nielsen HA, Pinson P, Kariniotakis G, Siebert N, et al. Short-term wind power forecasting using advanced statistical methods. In: Proceedings of the 2006 european wind energy conference and exhibition; 2006.
[143] Al-Yahyai S, Charabi Y, Al-Badi A, Gastli A. Nested ensemble NWP approach for wind energy assessment. Renew Energy 2012;37:150–60.
[144] Lazić L, Pejanović G, Živković M. Wind forecasts for wind power generation using the Eta model. Renew Energy 2010;35:1236–43.
[145] Cheng WYY, Liu Y, Liu Y, Zhang Y, Mahoney WP, Warner TT. The impact of model physics on numerical wind forecasts. Renew Energy 2013;55:347–56.
[146] Larson KA, Westrick K. Short-term wind forecasting using off-site observations. Wind Energy 2006;9:55–62.
[147] De Giorgi MG, Ficarella A, Tarantino M. Assessment of the benefits of numerical weather predictions in wind power forecasting based on statistical methods. Energy 2011;36:3968–78.
[148] Lange B, Rohrig K, Ernst B, Schlogl F, Cali U, Jursa R, et al. Wind power prediction in Germany – recent advances and future challenges. In: Proceedings of the 2006 european wind energy conference and exhibition; 2006.
[149] Negnevitsky M, Potter CW.Innovative short-term wind generation prediction techniques. In: Proceedings of the 2006 IEEE PES power systems conference and exposition (PSCE); 2006. p. 60–5.